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ABSTRACT

Based on a human capital model, this paper uses household survey data from Peru to estimate differences between males and females in labor-market participation, productivity (measured in wages), and economic returns to education. The focus is on human capital, especially education, as a determinant of labor participation and productivity. The analysis used wage regression based on ordinary least squares and decomposition technique. The survey data identifies household characteristics (including landholding and unearned income) and market data, such as wages, that influence people's time allocation. Male wage earners are slightly more educated than women, except in some urban areas. Employed women, however, have more vocational training than employed men. Women generally receive lower real hourly wages than their male counterparts. Unearned income and landholding generally decrease the probability of labor-market participation for both. The data suggest that improving women's education can increase their labor market participation faster than increases in men's education would affect theirs. Financial returns for schooling are relatively higher for women than for men, especially at the secondary and postsecondary levels. The paper concludes: (1) that public education is less effective than private in raising productivity and reducing wage gaps; (2) that investment in women's education has numerous benefits; and (3) that households and communities are likely the main sources of gender bias regarding parental investment in children's education. (TES)

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WORKING PAPERS

Women in Development

Population and Human Resources
Department
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July 1990
WPS 461

Labor Market Participation, Returns to Education, and Male-Female Wage Differences in Peru

Shahidur R. Khandker

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Private schools are more effective than public schools in increasing productivity — and returns on female education are at least as high as returns on male education, so governments must find ways to improve the public schools and increase girls' schooling.

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Policy, Research, and External Affairs

WORKING PAPERS

Women in Development

WPS 461

This paper — a product of the Women in Development Division, Population and Human Resources Department — is part of a larger effort in PRE to determine if and how women's productivity (and thus family welfare) are improved when women are given more access to education, extension, training, credit, health care, and other public resources. Copies are available free from the World Bank, 1818 H Street NW, Washington DC 20433. Please contact Belinda Smith , room S9-125, extension 35108 (51 pages with tables).

Using household survey data from Peru, Khandker estimates differences between male and female participation in the labor market, productivity (measured by wages), and economic returns to schooling.

He tries to identify characteristics that enable some women, although not many, to participate in the labor market; to determine whether the private returns to education vary by gender and influence school enrollment; and to evaluate the extent to which the male-female wage gap is caused by differences in human capital.

Khandker reaches three policy conclusions:

- Public schools are less effective than private schools in raising productivity and reducing the wage gap. Policymakers should make the public school system more effective.

- Investments in education and training for girls increase their participation and productivity in the labor market more than a similar investment in boys' education increases theirs. Those investments also reduce fertility and improve the education of children and the health and nutrition of all family members. Returns are high on human capital investments in women — at least as high as an equivalent investment in men. The government must identify ways to channel more resources to women's education.

- Households and communities are probably the main sources of gender bias in parental investment in children's education, so the government must identify ways to influence the household's decisions about education. Policy research is needed to identify how households and communities affect parental decisions and how the government can intervene effectively to affect this decisionmaking.

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1. Introduction

This paper uses household survey data from Peru to estimate the differences between males and females in participation in the labor market, productivity (measured by wages) and economic returns to schooling. The purpose is to (a) identify those characteristics that enable some women, though not many, to participate in this sector, (b) determine whether the private economic returns to education vary by gender and influence school enrollment, and (c) evaluate the extent to which the male-female wage gap is caused by differences in human capital. Identifying the constraints to the labor market participation and productivity of women is particularly important in countries like Peru that have an underutilized female labor force.[1]

Results suggest that male-female differences in human capital (for instance, education) account for some observed differences in labor market participation and productivity. The results on returns to education show that the private rate of return is generally higher for women than for men, which appears inconsistent with lower school enrollment for girls than for boys, especially at the secondary level. When unobserved family characteristics that influence wage and return estimates are controlled, however, the results indicate that parents may have reasons, at least in rural areas, for investing less in daughters than sons. More research is necessary on the social and private benefits and costs of schooling to quantify the factors that influence this decision.

The paper uses a human capital model to analyze wages and labor market participation in the formal sector that was developed by Becker (1964)

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[1]See appendix table A1. Note that women's average labor force participation rate is lower in Latin America than in Asia and Africa (IDB 1987).

and Mincer (1974). The focus is on human capital -- especially education -- as a determinant of labor market participation and productivity. Because the amount of schooling imparts different skills -- and hence different wages -- this model provides a framework to look at differences in the wages and labor market participation of men and women in terms of levels of schooling. The wage estimates help determine the private rate of return to education for men and women. By comparing differences between men and women in school returns and school enrollments, we can see whether there is an underinvestment in the education of either gender. Furthermore, using the wage estimates, we can identify how much variation in wages is due to differences in human capital.

The wage function and the estimates derived from this may suffer from two sources of bias. The first source is unobserved variable problem bias, which arises in the event that some variables may affect wages but are not included in the wage regression. A satisfactory analysis, therefore, requires identifying potentially observable characteristics other than human capital that can affect an individual's wage. These are not clearly understood and thus difficult to incorporate in the analysis (Schultz 1989). There are, however, ways to reduce the impact of unobserved characteristics on wages and other related estimates. This paper uses a household fixed-effect method to quantify the severity of the bias in the estimates due to the unobserved variable problem. The second source produces a sample selection bias, which arises due to restricting the analysis to wage workers, thus ignoring information on workers who do not participate in the wage market. The paper identifies whether sample selection correction modifies the wage estimates and hence the difference in the economic returns of men and women to education and productivity.

Two earlier studies using the same household survey data from Peru have investigated the wage rate function for men and women (Stelcner and others 1988, King 1988). They did not, however, assess differences in wages and returns to schooling, or evaluate whether correcting for sample selection or unobserved variables systematically modifies the comparison of the estimated returns to education and productivity of men and women.

The paper is structured as follows. Section Two explains the model specification and estimation strategy. Section Three discusses the data and highlights the differences between males and females in terms of wage-related characteristics. Section Four reports the results. Policy implications are in the concluding section.

2. Model Specification and Estimation Strategy

This section outlines a model framework to address participation in the labor market, the private economic returns to education, and a wage gap between males and females that is influenced by differences in job-related characteristics. It also discusses ways to reduce the impact of unobserved variable and sample selection bias from the wage estimates.

2.1. Labor Market Participation

What influences women's participation in the labor market? Do women differ from men in responding to labor market opportunities? Does human capital (for instance, education) help women more than men to participate in the wage sector? Do women face different constraints? Identifying these factors will help policymakers promote the participation of women in the labor market.

The decision to join the labor market, given the constraints, is based on an individual's income-leisure trade-off. A household model framework can help identify the constraints that affect an individual's allocation of time (Becker 1965). This model identifies those individual characteristics, such as education and experience, household characteristics, including landholding and unearned income, and market conditions, such as wages, that influence an individual's allocation of time. Thus the time allocated to different activities, including leisure, can be drawn as a function of individual, household, and market characteristics. The time allocation data can produce a discrete choice structure of whether to participate in the wage market. The decision can be estimated using a probability function independently for males and females as follows:

$$Y_m = \tau_{om} + X_m\tau_{1m} + Z_m\tau_{2m} + e_m \qquad (1)$$

$$Y_f = \tau_{of} + X_f\tau_{1f} + Z_f\tau_{2f} + e_f \qquad (2)$$

where: $Y_j(j=m,f)$ are binary dependent variables with 1 if jth individual participates in the wage labor market and 0 otherwise; X is a vector of individual characteristics that influences an individual's time allocation; Z is a vector of household and market factors which also explains why an individual participates in the labor market; τ is the vector of coefficients

to be estimated, and e is an error term.[2]

Different reasons can justify the inclusion of individual (X), and household and market (Z) factors as explanatory variables in labor market participation equations (1)-(2). An individual characteristic, such as the level of education can be treated as an explanatory variable that may indicate the potential productivity of an individual at home and in market production. Holding market wages constant, an increase in the level of an individual's education can increase his or her probability of labor market participation if it increases the opportunity costs of staying at home. The household's constraints include such household asset variables as landholding, which may act as a proxy for productive household assets. The productive assets exert a price effect and an income effect on an individual's labor market participation. The price effect would raise the marginal product or "shadow price" of an individual's labor, while the income effect would encourage an individual to consume more of his or her leisure -- even at its given opportunity cost. The household's unearned income -- another household characteristic -- can influence labor market participation via a pure income effect. Such market factors as market wages exert an income and a substitution effect on an individual's time allocation. Market factors may

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[2] Y_j equal to zero includes individuals who are either selfemployed in family business and farming or exclusively engaged in nonmarket home production. The results may be biased if selfemployment and nonmarket home production are not highly substitutable. This requires analyzing the degree of substitutability between selfemployment and nonmarket production (Khandker 1987). No analysis has been done with the PLSS data. We assume for simplicity that home production and selfemployment are highly substitutable so that we can lump these two categories into one category. Our interest here is to find out what influences labor market participation, not so much what influences women's labor force participation (which consists of both self-employment and labor market work for cash). We wish to study the factors that influence women's participation and productivity in the formal sector.

also include community variables, such as the household's proximity to community services (schooling, health, and banking services). These variables measure the impact on time allocation of implicit prices of many goods and services the household uses for production and consumption.[3]

How do we estimate the labor market participation equation? Because the dependent variable takes the value of 1 or 0 in both equations (1)-(2), the error structures yield heteroscedasticity, and hence the ordinary least squares produces inconsistent estimates. However, a maximum likelihood method called the probit technique can produce efficient estimates (Maddala 1983).

2.2. Returns to Education

Under certain assumptions, we can approximate the proportional increase in wages due to an additional year of schooling as a measure of the private economic rate of return to education (Mincer 1974). Mincer assumes the following: (i) the only cost of schooling for an individual is his or her forgone earnings; (ii) individuals enter the labor force immediately after completion of schooling; and (iii) each individual working of N years is independent of his or her years of education. With an additional assumption of a steady state with no productivity growth, we can write the present value of the life earnings of an individual with S years of schooling as follows:

$$V(S) = \int_{S}^{N} W(S)e^{-rtdt} = W(S)\frac{1}{r}(e^{-rs}-e^{-rN}) \qquad (2)$$

where r is the rate of discount indicating people's rate of time preference. If r is equal for every one (and N is large), one gets

$$V(S) = W(S)\frac{1}{r}e^{-rs} = Vo \text{ for all } S; \qquad (3)$$

[3]No information on any of these market factors is available except for rural areas. Thus Z variables include only household-level variables.

and the present value of income streams is equalized by everyone. The above can be rewritten as

$$W(S) = W_o e^{rs}, \text{ where } W_o = V_o r. \qquad (4)$$

Taking log on both sides, we have

$$\ln W = W_o + rS. \qquad (5)$$

W_o may be interpreted as the permanent labor income of a worker. Individuals facing a given market interest rate, r, choose that level of schooling that maximizes the present value of lifetime earnings. Thus r may represent the internal rate of return. But to the extent that Mincer's assumptions do not hold, the estimated r is an approximation of the internal rate of return. Measuring returns to education for different levels of education can assess whether different kinds of education improve labor productivity and provide information on the relative scarcity of different skills in a country. Moreover, comparing returns to education for men and women can help identify whether there is underinvestment in the education of either gender.

Specification (5) then justifies for using a semilogarithmic wage function to estimate the economic returns to education. As Becker (1964) and Mincer (1974) argue, variations in wages arise from differences in investment in human capital. Thus, equation (5) can be rewritten in an estimatible form:

$$\ln W_i = \alpha_{0i} + \beta_{1i} S_i + \beta_{2i} K_i + \beta_{3i} K^2_i + \epsilon_i \qquad (6)$$

where $\ln W_i$ is the natural log of the hourly wage rate of the ith individual (i=m for male, i=f for female wage worker); S is the individual's years of schooling, K is the individual's postschool experience (defined as age - S - school entry age, say, 6); K^2 is the individual's experience squared; α_o and β_j (j=1,2,3) are, respectively, the intercept and slope coefficients to be

estimated; and ϵ_i is the individual specific unobserved error. If the error is assumed to be normally and independently distributed, an ordinary least squares technique when applied to wage equation (6) yields an estimate of r--the proportional increase in the wages associated with one year of education.

As postschool experience increases, productivity and wages tend to rise. But further increases in postschool experience may lead to a decline in wages and productivity because of diminishing marginal returns. The concavity of the wage profile is thus captured by the quadratic experience terms.[4] According to human capital theory, education and experience are likely to have major effects on productivity.

Three adjustments in the functional form of wage equation (6) are necessary, however.[5] First, there is a possibility that distinct regional labor markets may behave differently and hence yield quite different estimates. Three distinct labor markets (metropolitan Lima, other urban areas, and rural areas) have already been identified (Stelcner and others 1988). The wage rate and labor market participation equations are estimated separately for men and women in these three regions. While this method is preferred where there is no interregional migration, such migration does occur as educated workers move to higher wage markets.

But interregional migration may bias estimates of the returns to education as well as labor market participation. In Latin American countries

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[4]Although information on job-specific experience is available, we cannot include it in the wage equation because it is an endogenous variable. In contrast, postschool experience is exogenous to the extent that the individual's education is parentally determined and hence predetermined.

[5]These three adjustments are also applied to the labor market participation equation (1) or (2).

as much as half the life-cycle returns of rural residents to schooling result from migrating to urban centers (Schultz 1988). The bias due to interregional migration could not be reduced even if the migrants' original location were known, because migration is a self-selection process. Using regional "shifters" in the wage equation (6) and in participation equation (1) or (2) fitted for the country as a whole, one can illustrate the potential severity of interregional migration on the estimated returns to schooling and labor market participation. In particular, because high-wage urban regions have more and better schooling, introducing regional shift variables in the wage or labor market participation equation reduces the estimated returns to schooling, or the influence of schooling on participation in the labor market.

Second, an adjustment is necessary to quantify the effect of the quality of education on wages. Since different levels of school impart different skills and wages, it would be misleading to treat schooling as homogenous. Thus we include splines of schooling and years of education (both general and technical) in the wage function (6) or labor market participation (1) or (2) to account for the heterogenous quality of education.

Third, an adjustment is also necessary to control for the effect on wages or labor market participation of the quality of education that individuals receive in private and public schools. The paper includes attendance or nonattendance in public school in the wage and participation functions to control for the influence of unobserved school quality. Parental characteristics often contribute to children's unobserved ability by giving them a better education (Schultz 1988). Thus by including this school quality variable in wage function (6), for example, we can reduce the impact of parental characteristics on an individual's productivity and hence returns to

education.[6]

Two additional adjustments may be necessary to estimate a wage function free from unobserved variable and sample selection bias. Omitted variables such as individual ability may overestimate school returns if school attainment is correlated with an individual's unobserved ability. Excluding unobserved individual ability variables may not seriously bias the wage estimates.[7] However, the unobserved household and community characteristics that often relate to abilities, motivation, quality of schooling, employment opportunities, and role models can influence wages and returns to education. More specifically, if these unobserved factors are correlated with years of schooling, the standard estimation procedure results in biased estimates of the impact of schooling and hence the returns to education (Behrman and Deolalikar 1988).[8] A fixed-effect method is used here to estimate the wage equation (6) to control for household and community heterogeneity.

This paper also adjusts the wage estimates for sample selection

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[6]One may include parents' characteristics directly in the wage regression. Stelcner and others (1988) report that the wage regression that excludes parents' education overestimates returns to schooling by about 3 percent for males in Peru. They also find a strong correlation between the father's education and public school attendance.

[7]Griliches (1977) observes that the coefficient of education derived from simple earnings functions that do not control for the unobserved ability is not likely to be biased by more than 5 to 10 percent. Willis (1986) argues that with an assumption of random choice among indifferent alternatives of occupation one can regress schooling on wages and get a consistent wage estimates even if ability (included in the error term) is unobserved.

[8]Behrman and Deolalikar (1988) found that these characteristics substantially influenced the wage estimates and hence returns to education. They did not, however, correct the wage estimates for the sample selection bias that arises for why a particular individual participates in the labor market.

bias that arise for endogeneity of the decision to participate in the labor market. Although the question of what determines an individual's level of education can be ignored by assuming that it is not a matter of choice but instead is chosen by the individual's parents, productivity cannot be independent of the worker's labor-leisure choice. Thus sample selection bias arises in equation (6), if it is estimated by ordinary least squares to include only wage-earners--thus excluding persons not reporting a wage yet part of the potential labor force. In Peru about 36 percent of all working males and about 18 percent of all working females are in the formal wage sector. The decision to join the labor market influences wages because the characteristics that affect labor market participation may also interact with wages. Thus the wage estimates need to be independent of the possible impact of these characteristics.

Estimating (6) in conjunction with labor market participation equation (1) or (2) may reduce sample selection bias from the wage estimates. Heckman (1979) has suggested a two-step procedure to estimate the wage and labor market participation equations. In the first stage the expected values of the residuals of (6) that are truncated are obtained by estimating the labor market participation by the probit method. By introducing the estimated values of residuals from the participation equation into wage equation (6), we can use ordinary least squares to estimate the wage function in the second stage. Heckman's two-step procedure yields consistent but efficient estimates, however. The reason for this is that the unobserved characteristics that influence labor market participation may also influence wage rates, that is, the correlation between the wage rate and participation errors is not zero. A maximum likelihood method, which jointly estimates the

wage rate and probit functions by taking into account the correlation between the errors of wage and participation equations, yields consistent and efficient estimates.[9]

An identification problem emerges, however. The variables that explain wages may also explain individual labor market participation. That is, the vector X and Z in (1) or (2) contains the variables included in the wage equation (6). Thus we need some identifying variables in equation (1) or (2) not included in the wage equation (6) to help distinguish a participant from a nonparticipant.

Three variables are considered here as potential candidates for identifying labor market participation equation (1) or (2) from the wage equation (6). The first two variables are included in vector Z: landholding and unearned income. Both are expected to influence the likelihood that a person will work for wages by affecting the person's reservation wage: If an individual has a considerable amount of land or unearned income, he or she will be less likely to work for wages because the returns in other activities are higher. These two variables are expected to influence only labor market participation -- not wages. The third identifying variable is marital status which is included in X vector of the participation equation (1) or (2). Married couples can specialize more easily than unmarried individuals, which usually encourages married men to work for wages and married women to work in

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[9]Note that estimating wage equation (6) without accounting for labor market participation (1) or (2) produces sample selection bias, but it is difficult to ascertain a priori the direction in which sample selection bias correction would alter the wage estimates.

the home (Schultz 1988).[10] Marital status thus can influence labor market participation, but not an individual's market productivity.[11]

2.3. Male-Female Wage Differences

A standard procedure to measure the male-female wage gap is to fit equation (6) by ordinary least squares to a sample of male (m) and female (f) workers:

$$\ln W_m = X_m \beta_m + \epsilon_m \qquad (7)$$

and

$$\ln W_f = X_f \beta_f + \epsilon_f \qquad (8)$$

where: β_m and β_f are the vector of unknown coefficients, including the intercepts, to be estimated; X_m and X_f are, respectively, the vector of males' and females' observed characteristics; and ϵ_m and ϵ_f are, respectively, the males' and females' individual specific error. A property of ordinary least squares is that the regression lines pass through the mean values of the variables so that

$$\ln \bar{W}_m = \bar{X}_m \hat{\beta}_m \qquad (9)$$

$$\ln \bar{W}_f = \bar{X}_f \hat{\beta}_f \qquad (10)$$

The hats denote the estimated values of the coefficients.

By simple manipulation of (9) and (10) the male-female wage gap function can be written as

$$\ln \bar{W}_m - \ln \bar{W}_f = \hat{\beta}_m (\bar{X}_m - \bar{X}_f) + (\hat{\beta}_m - \hat{\beta}_f) \bar{X}_f$$

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[10]Ideally, one would like to include such spouse characteristics as age and education, instead of marital status, to explain labor market participation. This information is not available for unmarried persons.

[11]Note that marital status may influence productivity and participation in the informal sector (self-employment) because of the compatibility between informal work and marital status.

$$- \hat{\beta}_f (\bar{X}_m - \bar{X}_f) + (\hat{\beta}_m - \hat{\beta}_f) \bar{X}_m \qquad (11)$$

where the first part of the right-hand side of equation (11) measures the wage gap due to male-female differences in wage-related characteristics and the second part measures the gap explained by the differences in male-female wage structures for the same observed job-related characteristics. As we can see in (11), one can measure wage gap in two ways: using the male wage structure or alternatively, using the female wage structure.[12]

A large number of studies using this decomposition technique (11) find that only a portion of the wage gap is explained by differences in human capital and other observed job-related characteristics (Becker 1985, Gronau 1988, Mincer and Polacheck 1974, Oaxaca 1973, Gannicott 1986). One can, in principle, make an accurate assessment of male's and female's productivity and hence in observed wages and private economic rates of return to education if one can measure their true productive capacities as perceived by employers. For various reasons, however, econometricians cannot include in the wage equation (6) all the variables that might influence individuals' productivity. Such unobserved characteristics as individual, family, or job-specific heterogeneity can make certain workers more productive than others.

This paper uses a household based sample selection procedure to

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[12]Naturally the two procedures do not yield the same answer. Thus as the decomposition technique assumes a particular (either male or female) wage structure to calculate the wage gap, this method introduces a group bias in the intragroup wage comparison. To the extent that both male and female wages are affected by discrimination, Neumark (1988) shows how a weighted average of the male and female coefficients may approximate the competitive wage that would prevail in the absence of discrimination. Note also that the second component of equation (11) is often taken as reflecting wage discrimination. However, because it is difficult to remove the effects of all possible wage-determining factors, including those that may reflect female discrimination outside the labor market, one cannot possibly attribute the second component as a measure of discrimination (Gunderson 1989).

estimate the wage gap between men and women.[13] Samples are chosen from households where at least one male and one female participate in the labor market. The restricted samples are comparable and hence may reduce the bias of unobserved household characteristics.[14] Using wage regression (6) and decomposition technique (11), we calculate the wage gap for this restricted sample and compare it with the one where full samples are used to estimate the wage gap. This technique, however, suffers from both sample selection and group bias. Sample selection bias is corrected but not the group bias in this decomposition method.

The group bias, however, does not arise if we use a household fixed-effect method to estimate directly the wage gap, for the fixed-effect method does not need a particular wage structure. Moreover, the unobserved household and community characteristics that influence interfamily wage estimates no longer affect the estimates. To see how this method works, consider the following. Let

$$\ln W_m = X_m \beta_m + \epsilon_{fam} + \epsilon_m \qquad (12)$$

and

$$\ln W_f = X_f \beta_f + \epsilon_{fam} + \epsilon_f \qquad (13)$$

be the wage equations, respectively, for males and females, where ϵ_{fam} is the

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[13]One can, alternatively, restrict samples to a particular occupation (for instance, Birdsall and Fox (1985) for teaching) or to never married males and females whose household responsibilities (unobserved) are more similar than married individuals (Mincer and Polachek 1974, Robb 1978). This method, which reduces the impact of unobserved individual motivation or profession-related characteristics on the wage estimates, underestimates the wage gap for a random male and female with the same observed characteristics (Gunderson 1989). This procedure, therefore, must account for the sample selectivity bias.

[14]This method still suffers from unobserved variable bias. What this sample selection technique does is to reduce the intensity of the unobserved motivation or role models on the wage estimates, but does not remove their impact.

unobserved family- and regional-specific error, and other variables are as defined earlier.

Taking difference of (12) and (13) yields the following:

$$\ln W_{mf} = \ln W_m - \ln W_f = X_m \beta_m - X_f \beta_f + \epsilon_{mf} \qquad (14)$$

where the family- and regional-specific unobserved effects cancel out and ϵ_{mf} is the error structure of the log wage differentials, $\ln W_{mf}$.

Model (14) estimates how much job-related characteristics explain male-female wage differences, assuming that wage structures for men and women are different. Thus, the unobserved household and regional characteristics that affect the interfamily wage estimates do not influence the intrafamily wage estimates. Moreover, differencing out male's and female's wages at the household level, unlike the decomposition method of (11), does not assume any particular wage structure to estimate the wage gap.

However, if we assume that males and females receive the same returns for the same characteristics, equation (14) can be rewritten as:

$$\ln W_{mf} = (X_m - X_f)\ \delta + \epsilon_{mf} \qquad (15)$$

whence $\delta = \beta_m = \beta_f$.

By comparing models (14) and (15) it is possible to estimate how much of the wage gap is due to differences in the wage structures of men and women. Moreover, the model (15) can identify individual sources of variation that is explained by job-related characteristics.

Nevertheless this household fixed-effect method suffers from sample selection bias. To obtain efficient estimates of (14) or (15), we correct them for not only why an individual participates in the labor market but also why a particular male and a particular female from a particular household participate in the labor market. Correcting the second source of

bias depends on the correlation of the error structures, e_m and e_f, in the participation equations of (1) and (2). If e_m and e_f are correlated which is likely the case, a joint estimation of the male-female wage gap equation (14) or (15) along with participation equations (1) and (2) must account for this correlation to yield efficient estimates.

3. Data Characteristics

The data used for this paper are drawn from the Peruvian Living Standard Survey (PLSS) household data collected jointly by the World Bank and the Peruvian Instituto Nacional de Estadistica (INE). These data provide detailed socioeconomic information on over 5,100 households and 26,000 individuals. The samples were drawn from a self-weighted national probability sample of Peruvian households and represent an approximate 1/100 sample of the population. The sampling frame is based on a 1984 National Health and Nutrition Survey. About 25 percent of the households in the PLSS were located in metropolitan Lima, 28 percent in other urban areas, and 47 percent in rural areas. The data were collected between June 1985 and July 1986 (see Grootaert and Arriagada 1986).

This paper covers workers aged 14 to 60. The wage earner participation equation is estimated using information for all potential workers. The wage equation, however, is estimated only for those men and women who reported wage remuneration and hours worked in the wage sector as their main occupation during the week prior to data collection. Thus self-employed and unpaid family workers are excluded from this reduced sample. The wage sample consists of 2,255 men from 1,856 households and 898 women from 783 households, drawn from a total of 6,429 men from 4,142 households and 6,942

women from 4,387 households. Among the men, 994 from 789 households work in metropolitan Lima, 731 from 610 households work in other urban areas, and 530 from 457 households work in rural regions. Among the women, 485 from 403 households work in Lima, 281 from 262 households work in other urban areas, and 152 from 118 work households in rural Peru.[15] The wage labor market participation rate for women is 23 in Lima, 13 in other urban areas, and 5 in rural areas -- an average of 13. The rate for men is 53, 38, and 21, or an average of 35. Table 1 gives the means and standard deviations of the variables by gender and by region.

Male wage earners are slightly more educated than women except in other urban areas. But employed women have more vocational training than employed men in all regions.[16] Women also come from relatively wealthier households (in terms of landholding and unearned income) and are the offspring of better-educated parents. The data suggest that more married (or cohabiting) men participate in the labor market than married (or cohabiting) women. And women generally receive lower real hourly wages than their male counterparts.[17] Women's earnings, for example, are two-thirds of men's wages in Lima, a fifth of men's wages in other urban areas, and a half in the

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[15]Note that rural women who participate in the formal sector are mainly salaried, like school teachers, and hence the difference in wages or characteristics may not be substantial.

[16]Women receive vocational training for occupations where women dominate, such as secretarial jobs (Arriagada 1989). This affects comparisons of men and women in terms of training.

[17]The real hourly wage rate, i.e., nominal hourly wages deflated at 1985 consumer price indices (RHW) is defined as RHW = AC/AH where:
AC = annual compensation = monthly pay x months worked in the past year;
AH = annual hours = weekly hours x months worked in the past year x 4.33.

country as a whole. Employed women are younger (measured by potential work experience, or age minus years of schooling minus 6), have less job-specific experience (although this variable is not used in the regression), and did not attend public school as long as their male counterparts. These differences in characteristics may explain part of the wage gap.

A comparison of the characteristics of employed and unemployed women as shown in appendix table A1 and table 1 suggests that the observed differences, with few exceptions, are consistent throughout the country. Education increases the participation of women in the wage sector. Employed women have almost twice as much schooling as those who do not participate. The figures are similar for women with vocational training. Fifty-two percent of women wage earners had such training, while only 20 percent of those who do not participate have had training. Seventy-eight percent of participating women attended public rather than private schools, compared to 68 percent of nonparticipating women. A higher percentage of married women do not participate in the labor force (58 percent) compared to 41 percent who are in the labor market. The parents of women in the labor force are, on average, more educated than the parents of nonparticipating women. And nonparticipating women are from wealthier families (in terms of landholding).

Table 1. Mean Characteristics of Full Sample Male and Female Wage Earners

Variable description	All Peru		Lima		Other urban areas		Rural	
	Male	Female	Male	Female	Male	Female	Male	Female
Number of observations	2255	898	994	485	731	281	530	132
Log real hourly wage rate a/	1.340	1.158	1.606	1.289	1.343	1.268	0.838	0.446
	(0.934)	(0.966)	(0.806)	(0.868)	(0.890)	(0.881)	(1.010)	(1.161)
Years of potential work experience	18.902	15.614	17.398	14.519	19.172	15.569	21.351	19.727
	(12.620)	(11.124)	(12.156)	(10.567)	(12.351)	(10.095)	(13.430)	(13.982)
Years of job-specific experience	7.296	5.047	6.698	4.166	7.822	5.832	7.691	6.615
	(8.293)	(6.621)	(7.956)	(5.677)	(8.315)	(6.925)	(8.808)	(8.481)
Education								
Years of primary school	4.502	4.506	4.867	4.775	4.653	4.679	3.608	3.144
	(1.223)	(1.290)	(0.614)	(0.853)	(0.968)	(1.009)	(1.814)	(2.079)
Years of secondary school	2.870	3.398	3.680	3.746	2.881	3.754	1.336	1.356
	(2.271)	(2.187)	(1.948)	(1.978)	(2.269)	(2.043)	(2.038)	(2.112)
Years of postsecondary school	0.841	1.110	1.097	1.027	0.862	1.537	0.332	0.508
	(1.797)	(1.944)	(2.014)	(1.903)	(1.781)	(2.149)	(1.179)	(1.356)
Vocational training	0.309	0.518	0.406	0.645	0.321	0.473	0.109	0.144
	(0.462)	(0.500)	(0.491)	(0.479)	(0.467)	(0.500)	(0.313)	(0.352)
Secondary technical diploma	0.024	0.031	0.029	0.039	0.023	0.032	0.015	0.000
	(0.153)	(0.174)	(0.168)	(0.194)	(0.151)	(0.176)	(0.122)	(0.000)
Postsecondary diploma	0.032	0.074	0.030	0.060	0.047	0.103	0.017	0.061
	(0.177)	(0.261)	(0.171)	(0.237)	(0.211)	(0.171)	(0.129)	(0.239)
University diploma	0.082	0.117	0.112	0.107	0.073	0.171	0.038	0.038
	(0.274)	(0.322)	(0.315)	(0.309)	(0.259)	(0.377)	(0.191)	(0.192)
Attended public school	0.847	0.758	0.833	0.740	0.889	0.836	0.815	0.659
	(0.360)	(0.428)	(0.373)	(0.439)	(0.314)	(0.371)	(0.389)	(0.476)
Father's education	4.639	5.551	5.550	5.922	4.677	5.851	2.881	3.553
	(3.374)	(3.369)	(3.340)	(3.367)	(3.331)	(3.269)	(2.758)	(2.875)
Mother's education	2.909	3.449	3.632	3.621	2.854	3.673	1.628	2.349
	(2.752)	(2.663)	(2.878)	(2.629)	(2.706)	(2.735)	(1.999)	(2.364)
Total years of school	8.212	9.013	9.644	9.549	8.395	9.972	5.276	5.008
	(4.143)	(4.272)	(3.521)	(3.604)	(3.939)	(4.129)	(3.991)	(4.617)
Married or cohabiting	0.624	0.408	0.577	0.400	0.673	0.434	0.643	0.379
	(0.485)	(0.492)	(0.494)	(0.490)	(0.469)	(0.497)	(0.479)	(0.487)
Unearned real income x 1,000	2.164	2.980	3.008	3.975	1.561	2.258	1.411	0.858
	(11.433)	(8.555)	(9.319)	(10.822)	(4.859)	(4.814)	(18.945)	(3.092)
Landholding (hectares)	1.624	1.673	0.060	0.096	0.374	4.354	6.282	1.757
	(19.770)	(35.328)	(1.095)	(1.128)	(2.546)	(63.031)	(40.32)	(4.999)

Note: Numbers in parentheses are standard deviations.
a/ Intis at June 1985 prices.

4. The Results

This section reports the results on labor market participation, returns to education, and male-female wage differences in Peru. First, it highlights the determinants of men's and women's participation and productivity in the formal sector. Second, it discusses the estimated returns to education for men and women. Third, it reviews the relationship between returns to education and school enrollment for boys and girls to see whether parents respond to private economic returns to education in sending children to school. Fourth, it discusses the estimates of the wage gap between men and women to examine the extent to which the human capital model explains the wage gap in Peru. We conclude that unobserved family and community characteristics have an important influence on wages, returns to education, and wage differences between males and females.

4.1 Determinants of labor market participation and productivity

Tables 2 and 3 report four wage rate specifications for men and women in each region and in the country as a whole. Also included are four probit equations that examine the probability that an individual will join the wage sector. Based on the Likelihood Ratio test, the hypothesis that marital status has no effect on labor market participation is rejected. Tables 2 and 3 are based on the preferred specification that includes marital status as well as landholding and unearned income as identifying variables in the probit equation.

Consider first the decision to join the labor market. Both general and technical education affect this decision. Vocational training and secondary education, however, increase women's labor market participation more than men's. Thus in Peru as a whole, the probability that a woman will join

the formal wage market is about 10 percent higher if both men and women have vocational training. On the other hand, the probability that a woman will join the wage market is at least 5 percent higher if both women and men complete secondary school. This suggests that improving women's education can increase their labor market participation faster than a similar increase in men's education would affect their participation. Public school attendance is an important determinant of men's labor market participation, but not of women's. Both unearned income and landholding (which measure the income effect on leisure) generally decrease the probability of being in the labor market for both men and women. Landholding significantly reduces men's participation in the work force in all regions, but only affects women's participation in rural areas. Labor force participation for both genders is lower outside of Lima: 31 and 49 percent lower for women in other urban areas and rural areas respectively, and 33 and 74 percent lower for men in corresponding areas. This indicates that there is a higher probability that women will work for wages than men.

Table 2. Maximum Likelihood Estimates of Probit and Wage Equations for Male Wage Earners

Explanatory description	Lima		Other Urban Areas		Rural Areas		All Peru	
	Probit	Wage Rate	Probit	Wage Rate	Probit	Wage Rate	Probit	Wage Rate
Constant	-0.949	0.804	-0.947	0.615	-1.128	-0.829	-0.784	0.269
	(-4.074)	(2.912)	(-5.494)	(3.101)	(-8.413)	(-2.025)	(-8.176)	(0.755)
Potential work experience	0.062	0.039	0.074	0.022	0.037	0.044	0.059	0.043
	(6.153)	(4.047)	(7.744)	(2.242)	(3.614)	(2.947)	(10.062)	(3.522)
Potential work experience squared x 100	-0.123	-0.045	-0.154	0.014	-0.075	-0.071	-0.117	-0.048
	(-5.951)	(-2.214)	(-7.862)	(0.672)	(-4.069)	(-2.489)	(-10.382)	(-2.014)
Education								
Years of primary school	-0.012	0.040	-0.021	0.101	0.017	0.062	0.005	0.093
	(-0.254)	(0.996)	(-0.617)	(2.943)	(0.679)	(1.625)	(0.290)	(5.629)
Years of secondary school	0.049	0.079	-0.004	0.119	0.058	0.088	0.033	0.088
	(2.508)	(5.521)	(-0.206)	(6.488)	(2.739)	(2.597)	(3.013)	(7.309)
Years of postsecondary school	0.059	0.080	-0.016	0.070	0.171	0.255	0.019	0.088
	(2.233)	(4.351)	(-0.526)	(1.984)	(2.270)	(3.510)	(0.988)	(5.039)
Vocational training	0.196	0.161	0.315	-0.068	0.297	0.616	0.263	0.166
	(2.908)	(3.405)	(4.782)	(-0.951)	(2.555)	(4.342)	(5.788)	(2.842)
Secondary technical diploma	-0.018	0.016	0.287	0.042	0.691	0.426	0.230	0.068
	(-0.091)	(0.101)	(1.241)	(0.221)	(1.916)	(1.083)	(1.706)	(0.586)
Postsecondary diploma	0.328	0.164	0.676	0.017	-0.315	0.169	0.481	0.227
	(1.524)	(1.055)	(3.308)	(0.070)	(-0.754)	(0.178)	(3.518)	(1.367)
University diploma	0.061	0.384	0.491	-0.056	0.039	0.366	0.377	0.326
	(0.372)	(3.609)	(2.327)	(-0.235)	(0.085)	(0.879)	(3.084)	(2.884)
Attended public school	0.279	-0.199	0.008	-0.059	-0.187	-0.098	0.069	-0.101
	(3.403)	(-2.994)	(0.086)	(-0.594)	(-1.898)	(-0.707)	(1.293)	(-2.027)
Unearned income x 1000	-0.004		-0.001		0.005		-0.003	
	(-1.596)		(-0.286)		(0.666)		(-1.451)	
Landholding	-0.033		-0.034		-0.020		-0.001	
	(-1.624)		(-6.689)		(-2.587)		(-2.769)	
Married or cohabiting	0.197		0.194		0.020		0.134	
	(2.339)		(2.966)		(0.256)		(2.803)	
Residence - other urban area	-		-		-		-0.329	-0.136
	-		-		-		(-7.572)	(-2.102)
Residence - rural area	-		-		-		-0.737	-0.297
	-		-		-		(-15.178)	(-2.240)
Standard error of wage function	0.629		0.653		0.838		0.751	
	(23.051)		(26.023)		(25.913)		(45.648)	
Correlation between wage earner and wage rate errors*	-0.282		-0.613		0.566		-0.133	
	(-1.982)		(-10.576)		(2.940)		(-0.528)	
Log-likelihood	-2208.85		-1986.48		-1943.47		-6256.52	
Selected sample (sample size)	994 (1901)		731 (1941)		530 (2587)		2255 (6429)	

Note: Numbers in parentheses are t-statistics.
*The sign of the coefficients determine the correlation between wage earner and wage rate errors.

Table 3. Maximum Likelihood Estimates of Probit and Wage Equations for Female Wage Earners

Explanatory description	Lima		Other Urban Areas		Rural Areas		All Peru	
	Probit	Wage Rate	Probit	Wage Rate	Probit	Wage Rate	Probit	Wage Rate
Constant	-1.205	-0.449	-2.202	-1.398	-2.037	-1.260	-1.614	-0.832
	(-6.105)	(-1.147)	(-11.002)	(-2.535)	(-9.819)	(-1.029)	(-14.218)	(-2.776)
Potential work experience	0.065	0.073	0.110	0.124	0.047	0.033	0.069	0.083
	(5.910)	(6.102)	(8.238)	(7.140)	(3.217)	(0.792)	(0.992)	(9.129)
Potential work experience squared x 100	-0.161	-0.130	-0.225	-0.232	-0.077	-0.063	-0.141	-0.150
	(-6.462)	(-4.073)	(-8.054)	(-5.802)	(-2.765)	(-0.766)	(-9.837)	(-7.100)
Education								
Years of primary school	-0.038	0.065	-0.029	0.083	0.110	0.083	0.012	0.094
	(-0.950)	(1.576)	(-0.695)	(1.201)	(2.589)	(0.825)	(0.546)	(3.629)
Years of secondary school	0.048	0.132	0.123	0.169	0.047	0.125	0.081	0.146
	(2.204)	(5.648)	(4.954)	(5.228)	(1.096)	(1.113)	(5.528)	(7.427)
Years of postsecondary school	0.042	0.098	0.109	0.093	0.192	0.268	0.076	0.100
	(1.228)	(2.837)	(2.623)	(1.400)	(1.770)	(1.018)	(3.073)	(2.846)
Vocational training	0.462	0.254	0.306	0.116	0.086	0.272	0.357	0.217
	(6.106)	(2.184)	(3.330)	(1.083)	(0.475)	(0.717)	(6.599)	(2.834)
Secondary technical diploma	0.235	-0.019	0.486	-0.289	-	-	0.308	-0.078
	(1.245)	(-0.093)	(1.712)	(-1.028)	-	-	(2.028)	(-0.419)
Postsecondary diploma	0.709	0.363	0.461	0.272	0.953	0.330	0.663	0.359
	(3.448)	(1.859)	(2.077)	(0.975)	(1.863)	(0.328)	(4.804)	(2.083)
University diploma	0.662	0.246	1.012	0.076	0.595	0.312	0.809	0.203
	(3.201)	(1.189)	(4.125)	(0.217)	(0.901)	(0.240)	(5.441)	(1.047)
Attended public school	0.056	-0.299	0.144	-0.096	-0.179	-0.260	0.055	-0.231
	(0.655)	(-3.859)	(1.211)	(-0.753)	(-1.114)	(-0.690)	(0.910)	(-3.401)
Unearned income x 1000	-0.003		-0.014		0.006		-0.006	
	(-0.957)		(-1.552)		(0.437)		(-2.102)	
Landholding	-0.027		0.001		-0.029		-0.0001	
	(-0.984)		(0.598)		(-4.785)		(-0.225)	
Married or cohabiting	-0.490		-0.713		-0.614		-0.574	
	(-6.662)		(-7.710)		(-5.888)		(-11.943)	
Residence - other urban area	-	-	-	-	-	-	-0.310	-0.129
	-	-	-	-	-	-	(-5.958)	(-1.878)
Residence - rural area	-	-	-	-	-	-	-0.486	-0.427
	-	-	-	-	-	-	(-7.574)	(-4.575)
Standard error of wage function	0.690		0.669		0.983		0.749	
	(33.003)		(20.045)		(15.922)		(46.632)	
Correlation between wage earner and wage rate errors*	0.178		0.291		0.524		0.259	
	(0.863)		(1.585)		(1.172)		(1.929)	
Log-likelihood	-1507.06		-942.16		-653.38		-3179.06	
Selected sample (sample size)	485 (2069)		281 (2116)		132 (2757)		898 (6942)	

Note: Numbers of parentheses are t-Statistics.
*The sign of the coefficients determine the correlation between wage earner and wage rate errors.

The wage function for men and women is estimated by a maximum likelihood method using the probit estimates of labor market participation.[18] The wage estimates indicate that human capital variables explain a substantial portion of the variation in wages.[19] Among the important determinants of productivity, education and experience are crucial; returns to experience, however, are higher for women than for men. Education at all levels influences both men's and women's productivity in Peru, although the results vary by region. For example, primary school has no influence on productivity in Lima, while it has a significant impact, at least for men, in other urban and rural areas.

Technical education increases the labor market productivity of men and women. In Lima, women's wages increase by 25 percent and men's wages by 16 percent if they have had vocational training. But when gains from interregional migration are excluded, women's wage gains drop to 22 percent. In contrast, the wage increases of women with postsecondary diplomas do not change as a result of interregional migration. The returns to vocational training vary by region: wages of male workers with a secondary, postsecondary, or university diploma are 46 percent higher in rural areas than

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[18]When normality tests (that is, skewness and kurtosis tests) of the log wage errors are carried out, the normality assumption is rejected for both men and women. Although this finding has severe adverse effects on the t statistics of an OLS method, the asymtotic property of maximum likelihood method reduces the severity of non-normality of the wage errors. The non-normality of wage errors suggests, however, that individual, household, and community heterogeneity influence individual wages.

[19]The wage rate regression for rural women workers does not produce significance of any explanatory variable. This is not surprising, given the high standard error of the wage regression fitted for rural areas. The reason is perhaps because there are few women working in the wage sector in rural areas, and since most rural women work as teachers or clerks, the variation in wages is small.

in Lima. Conversely, the wages of male university graduates are 5 percent higher in Lima than in Peru as a whole. This suggests the importance of Lima as an industrial and financial center for university graduates (Stelcner and others 1989).

Workers in Lima are paid more than their counterparts with the same education in other areas, as seen in the all-Peru wage equation. In Lima, male and female workers earn about 13 percent more than workers in other urban areas, and men and women earn 30 and 43 percent more respectively than rural workers. This suggests that rural-urban migration is lower for women than for men. Rural women, however, while more likely to be in the wage sector than rural men, receive much lower wages.

In comparison with private schooling, the returns to public school attendance are lower for both male and female productivity. Wages in Lima are 20 percent lower for men and 30 percent lower for women who attended public school than for those who attended private school. When gains due to interregional migration are excluded, the wage differences fall to 10 percent for men and 23 percent for women, possibly due to less interregional mobility by women. The difference in the productivity of public versus private school graduates indicates that the public school system should be improved. This finding is consistent with other studies (Stelcner and others 1989, King 1988).

The sign of the coefficients of the correlation between wage earner and wage rate errors determines the type of selection that generates the group of workers. Tables 2 and 3 suggest that the most able men select nonwage employment in urban areas and wage employment in rural areas. Among women, on the other hand, the most able individuals seem to select wage

employment in all regions of the country. The results also indicate that unobserved characteristics that influence labor market participation have an important influence on individual productivity.

4.2. Estimates of Returns to Schooling

Table 4 presents three sets of estimates of returns to education: ordinary least squares, maximum likelihood (from tables 2 and 3), and household fixed-effect.[20] A comparison of ordinary least squares and maximum likelihood results suggests that the estimates are sensitive to sample selection correction. The estimated private rates of return to schooling increase somewhat for men and women when controls are introduced for sample selection bias.[21] Men gain only from education in rural areas because of sample selection correction. Thus for males in rural Peru the returns increase from 6 to 9 percent at the secondary level, and from 21 to 25 percent at the postsecondary level. Women, on the other hand, gain in all areas, especially at secondary and postsecondary levels. The returns for women at the secondary level increase from 15 to 17 percent in other urban areas and from 10 to 13 percent in rural areas when the maximum likelihood method is used to correct the sample selection bias. At the postsecondary level the increase for women is also notable: 10, 9, and 27 percent, compared to 9, 7, and 20 percent respectively in Lima, other urban areas, and rural areas.

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[20]The household fixed-effect method uses a generalized least squares technique based on Hausman Specification test which indicates that an error component method is appropriate after we introduce sample selectivity correction factor in the wage regression. Thus, the household fixed-effect estimates reported in Table 4 are free from both sample selection bias and unobserved variable bias due to household heterogeneity.

[21]This is, however, not the case for men in Lima regression.

Table 4. Estimates of Private Rates of Return to Schooling by Gender, Using Alternative Estimation Methods

Region / Estimation Method	Private Rates of Return by School Level					
	Primary		Secondary		Postsecondary	
	Male	Female	Male	Female	Male	Female
Lima Metropolitan Area						
Ordinary Least Squares	0.04	0.07	0.09	0.13	0.09	0.09
	(0.95)	(1.48)	(6.16)	(5.56)	(4.95)	(2.87)
Maximum Likelihood	0.04	0.07	0.08	0.13	0.08	0.10
	(1.00)	(1.58)	(5.52)	(5.65)	(4.35)	(2.84)
Household Fixed-effect	0.03	0.05	0.07	0.14	0.07	0.10
	(0.81)	(1.16)	(3.83)	(5.80)	(3.17)	(2.84)
Other Urban Area						
Ordinary Least Squares	0.10	0.08	0.12	0.15	0.07	0.07
	(2.70)	(1.54)	(7.07)	(4.90)	(2.51)	(1.79)
Maximum Likelihood	0.10	0.08	0.12	0.17	0.07	0.09
	(2.94)	(1.20)	(6.49)	(5.23)	(1.98)	(1.40)
Household Fixed-effect	0.09	0.09	0.11	0.17	0.06	0.10
	(2.46)	(1.55)	(6.24)	(5.10)	(2.29)	(2.29)
Rural Area						
Ordinary Least Squares	0.05	0.05	0.06	0.10	0.21	0.20
	(1.56)	(0.63)	(2.26)	(1.11)	(2.29)	(1.30)
Maximum Likelihood	0.06	0.08	0.09	0.13	0.26	0.27
	(1.63)	(0.83)	(2.60)	(1.11)	(3.51)	(1.02)
Household Fixed-effect	0.11	0.37	0.17	-0.02	0.42	0.26
	(3.20)	(5.73)	(3.46)	(0.26)	(3.27)	(1.66)
All Peru						
Ordinary Least Squares	0.09	0.09	0.09	0.13	0.09	0.09
	(5.08)	(3.06)	(8.98)	(7.28)	(5.61)	(3.30)
Maximum Likelihood	0.09	0.09	0.09	0.15	0.09	0.10
	(5.63)	(3.63)	(7.31)	(7.43)	(5.04)	(2.85)
Household Fixed-effect	0.10	0.10	0.07	0.15	0.07	0.11
	(5.35)	(3.25)	(5.30)	(7.98)	(4.30)	(3.82)

Both male and female educated workers gain if they migrate to urban areas. The gains are more substantial for men with a primary and secondary education if they migrate to other urban areas rather than to Lima. Similarly, women with a secondary education gain if they migrate to other urban areas from rural areas. The returns to schooling are, therefore, likely to be overestimated if the effect of interregional migration is not controlled for in the regional estimates. This is evident in the all-Peru wage estimates. When gains from interregional migration are excluded and sample selectivity bias is corrected, the private rates of return decrease for men and women.

The differences in returns to schooling for men and women are worth noting. In Lima the private rates of return at the primary school level are low, but higher for women than for men (7 percent compared to 4 percent).[22] At the secondary and postsecondary levels, however, the returns to schooling are high, and again, higher for women than for men: 13 and 10 percent respectively, compared to 8 percent in each case for men. In other urban areas the returns for men are 10 and 12 percent respectively at the primary and secondary levels, compared to 8 and 7 percent respectively for women. The returns drop at the postsecondary level for both genders in other urban areas -- to 7 percent for men and 9 percent for women. In contrast, the return to schooling is an increasing function of the level of education for both men and women in rural areas. If we exclude from the wage estimates gains due to migration, the private rate of return to schooling drops for men at the primary level and for both men and women at the secondary level, while increasing for both men and women at both postsecondary levels.

The returns to schooling are relatively higher for women than for men,

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[22]This pattern is different from that of Bogota (Mohan 1986).

especially at the secondary and postsecondary level. This finding contrasts with studies from other countries that suggest that the returns to schooling are similar for men and women (Schultz 1989). The return to schooling is higher for women at the secondary level than at any other level, however, a finding consistent with other Latin American and Asian countries (Schultz 1988; Mohan 1986).

Does the finding differ when we correct the estimates for unobserved variable bias? A comparison between maximum likelihood and household fixed-effect results indicates that if we do not control for unobserved household characteristics in the wage regression, the technique, even after controlling for sample selection bias due to the endogeneity of participation in the labor market, can produce biased estimates of returns to education. The estimates of returns to education, however, respond differently for men and women to the correction made for unobserved household heterogeneity. The results suggest that sample selection correction without correcting for the unobserved variable problem tends to overestimate the economic returns to the education of men while underestimating the returns to education of the women. There are exceptions to this finding, however. In particular, the correction for unobserved household heterogeneity in rural areas increases the returns to men's education at all levels of schooling but decreases the returns to women's education at the secondary and postsecondary levels. Moreover, when gains from interregional migration are excluded, the household fixed-effect method increases the returns to education for men at the primary level.

The household fixed-effect method, however, confirms the earlier findings that even if we correct the returns to education for unobserved household heterogeneity, the economic returns to education are higher for women than for men, and the return to schooling is higher for women at the secondary level than at other

levels.[23]

4.3. Returns to Education and School Enrollment of Children

Do parents respond to the private economic rate of return to education in sending their children to school? Parents invest in their children in the form of education. If parents make conscious investment decisions, then the private economic rate of return to education should influence the school enrollment of boys and girls.

Table 5 presents differences between males and females in school enrollment, and two estimates of private rates of returns to education--one based on maximum likelihood and the other on the household fixed-effect method (from table 4). As noted earlier, the maximum likelihood controls for sample selectivity bias, while in the household fixed-effect method we control for both unobserved family characteristics and sample selection rules. Both indicate that the returns to education are higher for women than for men, except in rural areas. The household fixed-effect estimates show that returns to education are higher for men than for women in rural areas at the secondary and postsecondary levels.

Table 5 indicates that the school enrollment ratio is favorable for boys -- especially at the secondary level -- in all areas, suggesting that more boys are enrolled in school than girls. This appears inconsistent with the observed male-female differences in returns to education. But in rural areas the school enrollment ratio, especially at the secondary and

[23]The economic returns to education, however, are higher for men than for women at the secondary and postsecondary levels in rural areas when correction is made for household heterogeneity.

Table 5. Male-Female Differences in School Enrollment and Private Rates of Return to Education

School Level	Male-Female Difference	Peru	Lima	OUA	Rural
Primary	School enrollment ratio	0.01	0.01	0.00	0.02
	Private rate of return I	0.00	-0.03	0.02	-0.02
	Private rate of return II	0.00	-0.02	0.00	-0.26
Secondary	School enrollment ratio	0.09	0.01	0.04	0.17
	Private rate of return I	-0.06	-0.05	-0.05	-0.04
	Private rate of return II	-0.08	-0.07	-0.06	0.19
Postsecondary	School enrollment ratio	0.03	0.01	0.00	0.07
	Private rate of return I	-0.01	-0.02	-0.02	-0.01
	Private rate of return II	-0.04	-0.03	-0.04	0.16

Note: School enrollment ratio is defined as the proportion of the school-aged children enrolled in school. The differences in returns to schooling are based on the estimates of ML (panel I) and household fixed-effect (panel II) from Table 4.

postsecondary levels, seems consistent with the higher returns recorded by boys. This is possible when unobserved household characteristics are accounted for in the wage estimates. Thus at the postsecondary level, school enrollment of boys is 7 percent higher than girls', which is consistent with 16 percent higher returns for boys than for girls. When the unobserved household characteristics are controlled, the results from rural areas suggest that there are reasons (unobserved) that influence the parents' decision to send more boys than girls to secondary and postsecondary schools.

So at least in rural areas, parents do respond to incentives dictated by the private rates of return to education. Does this mean that parents in other areas do not respond to the incentives given by the economic returns to education? We must recognize that the communities to which the households belong may differ in characteristics that are unobserved to the econometrician. The household fixed-effect estimates do not control for unobserved community heterogeneity in school quality and employment opportunities that may influence wages and hence interact with the parents' decision regarding school investment. The demand for educated workers may vary by type of jobs available in a particular locality, which may influence the wage estimates and the demand for schooling by gender. We do not control for demand factors in the wage regression. Further research is thus needed to find out whether estimates of returns to education are sensitive to the correction for such unobserved community characteristics as school quality, or such demand factors as job availability.

4.4. Determinants of Male-Female Wage Differences

Table 6 shows the overall interfamily wage variations between males and females explained by the human capital model under the ordinary least squares estimation method, with and without sample selection correction, for three sets of samples of men and women. The first set uses the full samples, the second set uses the husband-wife combinations, and the third set uses the combination of any male and female who both participate in the labor market from the same household. Sample selection correction is made in all cases using Heckman's two-step procedure, which has the ordinary least squares

property to calculate the male-female wage gap according to the decomposition technique of equation (11).[24]

The ordinary least squares results for the full samples of men and women wage workers explain nothing in terms of male-female differences in human capital variables. But when the sample is restricted by household, the ordinary least squares technique now explains a sizable portion of the differences in wages in terms of the differences in job-related characteristics. For example, the human capital model explains a variation of 31 percent in Lima, 39 percent in other urban areas, and 22 percent in the country as a whole for the restricted samples of husbands and wives (assuming that wives are paid according to husband's wage structure). The results indicate that a comparable sample analysis may be a better explanation of wage differences in terms of observable job-related characteristics than a noncomparable sample analysis.

But the ordinary least squares results suffer from sample selection bias. Does sample selection correction affect the estimates? Table 6 shows that sample selection correction remarkably changes both the noncomparable and comparable sample analysis. When the Heckman selection procedure is applied to the full samples, the decomposition technique (assuming that females are paid according to male's wage structure) explains 47 percent variation in Lima and 99 percent in the country as a whole.[25] In

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[24]The estimates are not shown for rural areas because of few samples. The wage estimates for the restricted samples are in appendix table A3 for husbands and wives, and in appendix table A4 for any male-female combination.

[25]This is an interesting finding because it does not include any controversial control variable in the wage regression. The wage function includes an additional variable--the sample selection correction factor--that accounts for the unobserved characteristics influencing labor market participation.

Table 6: Interfamily Estimates of Male-Female Wage Gap By Alternative Sample Selection and Estimation Methods Using Wage Equation (6) and Decomposition Technique (11).

Region/Sample Selection Rule	Sample Size		Percentage Explained By Human Capital Variables Using OLS Method			
			Without Sample Selection Correction		With Sample Selection Correction	
	Men	Women	(A)	(B)	(A)	(B)
A. METROPOLITAN LIMA						
Full samples	994	485	0	0	47	0
Restricted samples: Husband-wife combination	126	126	31	22	32	16
Restricted samples: Any male-female combination	332	315	15	7	17	25
B. OTHER URBAN AREAS						
Full samples	731	281	0	0	0	0
Restricted samples: Husband-wife combination	68	68	39	30	27	0
Restricted samples: Any male-female combination	145	128	25	36	0	63
C. ALL PERU						
Full samples	2,255	898	0	0	99	0
Restricted samples: Husband-wife combination	218	218	22	27	17	2
Restricted samples: Any male-female combination	535	502	11	12	0	10

Note: Two wage structures are used: (A) male wage structure, and (B) female wage structure.

contrast, when sample selection correction is applied to the restricted sample size, the model explains 32, 27, and 17 percent of the husband-wife wage differences respectively, in Lima, other urban areas, and all-Peru (assuming that wives are paid according to husband's wage structure). Sample selection correction with the restricted sample size appears to reduce the explanatory power of the model. Table 6 also suggests that the results are quite sensitive to which wage structure is used to calculate the wage gap. Nevertheless the results suggest that such unobserved family characteristics as motivation or household role models have an important influence in determining individual wages and hence in the estimates of the wage gap between men and women.

One can use the fixed-effect method, difference equations (14) or (15), to quantify the extent of the impact of unobserved household or community bias on these estimates. But we need to test whether the model (15) or (14) is more appropriate to explain the difference in wages between men and women for the restricted samples. An F-test for testing the equality of male's and female's wages rejects the null hypothesis for the full samples of men and women. In contrast, a similar test for the restricted samples cannot reject the hypothesis. This means that men and women participating in the wage sector from the same household face the same wage structure.

The fixed-effect model (15) is thus estimated for three areas and for two samples. A bivariate probit method is used to estimate the husband-wife difference equation, while Heckman's two probit method is used to estimate the male-female difference equation for any male and female combination. The difference is that unlike Heckman's two probit method, the bivariate method does not assume zero correlation between husband's and wife's

participation errors[26] (see table 7). They suggest that the fixed-effect method explains 17 percent in Lima, 24 percent in other urban areas, and 16 percent in Peru as a whole of the wage gap in terms of male-female differences in human capital characteristics. These explained variations are net of the unobserved family and community characteristics that influence an individual's wages. Thus a comparison of this finding with the one reported in table 6 for the same samples indicates the extent of the wage variation due to unobserved family and community characteristics. The results suggest that if the unobserved household and community characteristics are not controlled in the wage regression, the model -- even with sample selection correction -- may overestimate the effect of job-related characteristics on an individual's productivity as much as 25 percent.

Table 7 also shows the sources of variation in the wage gap. The estimates are not qualitatively different for husband-wife and any male-female combination. They indicate that differences in human capital variables are important sources of wage differences between males and females. For example, a 1 percent reduction in the gap between male's and female's schooling at the primary level reduces the wage gap by 7 percent in Lima and 5 percent in Peru as a whole. A 1 percent reduction in the gap between male's and female's schooling at the secondary level reduces the wage gap by 7 percent in other urban areas. Improving women's vocational training can also reduce the wage gap. A 1 percent reduction in the vocational training differential reduces the wage gap by 25 percent in Lima, 31 percent in other urban areas, and 19 percent in Peru as a whole. A similar percentage

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[26]The reason for not reporting bivariate probit results for any male-female wage difference equation is that the model did not converge. However, Heckman two probit method yields consistent estimates.

reduction in achieving a postsecondary diploma reduces the gap even further: about 58 percent in Lima, 40 percent in other urban areas, and 35 percent in Peru as a whole. A reduction in the gap between men and women who achieve a university diploma, though, although it reduces the gap in wages between wives and husbands by 36 percent in Lima, increases the wage gap by 66 percent in other urban areas. This suggests that the returns to a university diploma are lower in other urban areas than in metropolitan Lima.

Public school attendance seems to increase the wage gap. Thus an increase in the number of girls enrolled in public school (while reducing the gap between males and females in public school enrollment) increases the male-female wage gap. This is perhaps true, since as we have seen, the returns to a public school education are less than the returns to a private school education. These findings call for policies to make public schools more effective in raising productivity.

The effects of sample selection correction on the male-female wage gap are shown by the sign of the coefficients of the correlation between the wage earner and wage difference errors. In Lima and all-Peru, unobserved factors that increase the participation of married men in the wage sector (with wives in the labor force) increase the wage gap. In contrast unobserved factors that increase any male's (female's) participation in the labor market reduce (increase) the wage gap in Lima. The results also confirm that the unobserved characteristics that increase the market participation of husbands encourages their wives to participate in the labor market.

Table 7. Fixed-Effect Estimates of Male-Female Wage Differences in Peru

Variable description	LIMA		Other Urban Areas		ALL PERU	
	Husband-Wife Differences	Male-Female Differences	Husband-Wife Differences	Male-Female Differences	Husband-Wife Differences	Male-Female Differences
Log wage differences	0.417	0.352	0.154	0.203	0.315	0.287
Constant	0.029	0.178	0.115	-0.009	0.150	0.408
	(0.106)	(0.931)	(0.469)	(0.038)	(0.811)	(2.946)
Potential work experience	0.044	0.035	-0.022	0.033	0.019	0.023
	(1.262)	(2.673)	(0.491)	(1.567)	(0.763)	(2.095)
Potential work experience squared x 100	-0.072	-0.050	0.001	-0.022	-0.023	-0.023
	(0.957)	(1.721)	(1.022)	(0.489)	(0.433)	(0.949)
Education						
Years of primary school	0.091	0.072	0.093	0.081	0.034	0.053
	(1.211)	(1.617)	(0.802)	(1.567)	(0.737)	(1.592)
Years of secondary school	0.084	0.040	-0.002	0.068	0.031	0.032
	(1.321)	(1.664)	(0.034)	(1.689)	(0.632)	(1.599)
Years of postsecondary school	0.020	0.017	-0.016	0.033	0.030	0.018
	(0.439)	(0.719)	(0.258)	(0.676)	(0.693)	(0.829)
Vocational training	0.249	0.035	0.073	0.308	0.193	0.072
	(2.228)	(0.464)	(0.490)	(2.577)	(2.151)	(1.087)
Secondary technical diploma	-0.066	0.053	-0.690	-0.569	-0.081	-0.094
	(0.296)	(0.267)	(1.412)	(1.214)	(0.302)	(0.501)
Postsecondary diploma	0.584	0.383	-0.125	0.402	0.361	0.349
	(1.839)	(2.277)	(0.427)	(1.674)	(1.546)	(2.545)
University diploma	0.355	0.208	-0.662	-0.314	-0.005	-0.070
	(1.949)	(1.375)	(2.111)	(1.237)	(0.026)	(0.522)
Public school	-0.202	0.025	-0.611	-0.280	-0.230	-0.044
	(1.408)	(0.300)	(3.127)	(1.800)	(1.916)	(0.611)
Correlation between male wage earner and wage difference errors	0.732	-0.318	1.029	0.027	0.671	-0.651
	(5.831)	(1.287)	(1.661)	(0.075)	(5.693)	(2.888)
Correlation between female wage earner and wage difference errors	0.019	0.312	0.132	0.098	-0.004	0.340
	(0.079)	(1.970)	(0.272)	(0.470)	(0.028)	(2.671)
Correlation between male wage earner and female wage earner errors	0.162		-0.922		0.196	
	(2.285)		(1.583)		(4.338)	
Residence - other urban area	-	-			-0.317	-0.195
			-	-	(2.725)	(2.378)
Residence - rural area	-	-	-	-	-0.289	-0.120
					(1.587)	(0.792)
Standard error of wage difference equation/F-Statistic	0.807	5.299	-	3.671	0.824	8.037
	(11.219)		-	-	(12.748)	
Selected sample (sample size)	126(860)	415(3369)	68(970)	153(3307)	218(3296)	637(10386)
R^2	0.07	0.14	0.21	0.24	0.15	0.15

Note: Table assumes that $\beta_m=\beta_f$; Absolute values of t-statistics are in parenthesis.

5. Discussion

This paper addresses a number of critical questions. First, does interregional migration affect wage estimates and thus estimated rates of return to education? The results show that interregional migration, when ignored, overestimates the returns to schooling. Interregional migration is perhaps more common for men than for women. Thus when gains from migration are excluded, the estimated returns to schooling decrease. The decline is sharper for men than for women. The results also suggest that both men and women can gain if they migrate from rural areas to other urban centers.

Second, what influences men and women to participate in the labor market? Although education and training raise labor market participation, but vocational training and secondary school increase the labor market participation of women more than that of men. Thus improving education for women can increase their participation faster than a similar increase in men's education would affect the participation of men. Unearned income and landholding reduce the participation of both men and women. The probability of being in the wage sector is high for married men and low for married women, indicating an expected job specialization after marriage.

Third, what determines the productivity of men and women in the formal sector? Experience, education, and training are all effective. The quality of education is also significant: those employees educated in private schools are more productive than those with a public school education. Moreover there are sharp regional differences in productivity. Men and women from other urban areas and rural areas are paid less than their counterparts in Lima. The extent of male-female differences in productivity depends on the impact of sample selectivity bias.

Fourth, is there any systematic gender bias in the estimated returns to schooling if we ignore the possible sample selection rule of who is a wage earner? The results suggest that sample selection correction increases the returns to schooling for both men and women if we include the gains from interregional migration. When these gains are excluded, however, the sample selection correction reduces returns to schooling. Sample selection bias is substantial in rural areas for both men and women, showing that the selected wage earners are not a random sample. The magnitude and direction of the bias, however, vary by region and gender. For example, the returns to postsecondary education are more biased in rural areas because of the unrepresentative character of the sample. The returns to schooling are also more biased for women in Lima at the primary school level. The results confirm that sample selection bias is an important factor in labor market participation. The most able men select nonwage employment in urban areas, while the most able men in rural regions -- and women in all areas -- are likely to select wage employment.

Fifth, is there any observable effect of unobservable family and community characteristics on the estimates of returns to education? Unobserved family characteristics, when controlled in wage regression, may reduce the returns to women's education. Thus when such bias is removed from the returns estimates, the returns to education may become <u>higher rather than lower</u> for males than for females. Hence there may be unobserved reasons for parents to send more boys than girls to school, especially at secondary and postsecondary levels.

And finally, why do men earn more than women? Although there are some differences in human capital, the extent to which these differences

explain the wage gap depends critically on sample selection correction factor as well as which wage structure is used to calculate the wage gap. Thus when sample selection correction is not included in the wage regression of a random sample of males and females, the human capital model does not explain the wage gap. When the correction factor is included, however, the model explains 47 percent of the wage gap in Lima and 99 percent in all-Peru, when we use the male wage structure to calculate the wage gap. This suggests that the unobserved characteristics that influence labor market participation and productivity also affect the productivity differences between males and females. In contrast, when the female wage structure is used, even with sample selection correction, the model explains nothing in terms of observed and unobserved characteristics. Sample selection correction is important, but may overestimate the effect of individual characteristics if the influence of unobserved family and community characteristics is not controlled. Clearly it would be useful to identify other observable characteristics that affect wage differences. Sample restriction to some extent increases the explanatory power of the human capital model, but involves sample selection bias and thus may not necessarily solve the puzzle of why women earn less than men.

Three policy implications that result from these questions. First, since public schools are less effective than private schools in raising productivity and reducing the wage gap, policymakers should make the public school system more effective.

Second, investments in education and training for women raise their participation and productivity in the labor market more than a similar investment in men's education. In addition, these investments reduce fertility and improve the education of children and the health and nutrition

of all family members. Thus human capital investment in women are a high return activity and at least as good as an equivalent investment in men. The government must identify ways to channel more resources to women's education.

Third, as households and communities are perhaps the major sources of gender bias in parental investment in children's education, the government must identify ways to influence the household's decision. Policy research will be required to identify how household and communities affect parental decisions and determine how the government can interact in this important decision making.

Further research is needed to address a number of related issues. The research issues are: How communities differ in characteristics (both observed and unobserved)? How do they influence the internal rate of return to education and hence the school enrollment of boys and girls? How can governments interact with parents' decision? What incentives are needed to encourage parents to send their daughters to school, especially at the secondary and postsecondary levels?

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APPENDIX: Table A1. Women's Labor Force Participation in Selected Latin American Countries: 1970-1980

Country	1970	1980
Argentina	24.9	26.9
Chile	22.4	27.3
Uruguay	26.3	29.6
Peru	20.3	24.2
Venezuela	20.7	25.8
Latin America	21.7	26.1

Source: IDB (1987) Economic and Social Progress in Latin America, 1987

APPENDIX: Table A2. Mean Characteristics of Nonparticipants by Gender in Peru

Variable definition	All Peru		Lima		Other urban area		Rural	
	Male	Female	Male	Female	Male	Female	Male	Female
Number of observations	4179	6044	907	1584	1210	1835	2057	2625
Years of potential work experience	18.450	20.859	14.111	18.033	15.349	18.724	22.188	24.057
	(15.09)	(15.081)	(13.562)	(14.494)	(14.499)	(15.098)	(15.152)	(14.815)
Years of job-specific experience	-	-	-	-	-	-	-	-
Education								
Years of primary school	4.057	3.340	4.807	4.455	4.631	4.053	3.388	2.169
	(1.603)	(2.090)	(0.747)	(1.339)	(1.045)	(1.681)	(1.854)	(2.120)
Years of secondary school	1.946	1.558	3.369	2.701	2.819	2.135	0.804	0.465
	(2.183)	(2.112)	(2.016)	(2.224)	(2.125)	(2.219)	(1.607)	(1.276)
Years of postsecondary school	0.328	0.201	0.641	0.376	0.542	0.295	0.064	0.029
	(1.112)	(0.870)	(1.513)	(1.176)	(1.365)	(1.026)	(0.516)	(0.344)
Vocational training	0.133	0.198	0.275	0.393	0.172	0.238	0.048	0.052
	(0.339)	(0.398)	(0.447)	(0.489)	(0.377)	(0.426)	(0.214)	(0.222)
Secondary technical diploma	0.009	0.009	0.021	0.023	0.010	0.009	0.003	0.004
	(0.099)	(0.095)	(0.143)	(0.151)	(0.099)	(0.096)	(0.054)	(0.019)
Postsecondary diploma	0.009	0.010	0.013	0.013	0.013	0.020	0.004	0.002
	(0.094)	(0.102)	(0.114)	(0.114)	(0.114)	(0.141)	(0.066)	(0.044)
University diploma	0.019	0.011	0.050	0.025	0.024	0.012	0.004	0.002
	(0.139)	(0.105)	(0.217)	(0.156)	(0.153)	(0.109)	(0.066)	(0.044)
Attended public school	0.833	0.682	0.773	0.764	0.891	0.798	0.826	0.550
	(0.373)	(0.466)	(0.419)	(0.425)	(0.312)	(0.402)	(0.379)	(0.498)
Father's education	3.899	3.929	5.432	5.466	4.684	4.561	2.761	2.559
	(2.898)	(3.076)	(3.099)	(3.226)	(2.619)	(2.959)	(2.369)	(2.410)
Mother's education	2.257	2.258	3.366	3.309	2.788	2.728	1.455	1.296
	(2.157)	(2.356)	(2.564)	(2.698)	(2.081)	(2.363)	(1.623)	(1.656)
Total years of school	6.331	5.099	8.817	7.533	7.509	6.483	4.257	2.664
	(3.856)	(4.100)	(3.248)	(3.636)	(3.509)	(3.885)	(3.102)	(3.057)
Married or cohabiting	0.498	0.578	0.376	0.519	0.439	0.550	0.587	0.634
	(0.501)	(0.494)	(0.485)	(0.499)	(0.496)	(0.498)	(0.493)	(0.482)
Unearned real income x 1,000	1.603	1.619	4.253	3.632	1.827	1.717	0.304	0.338
	(7.696)	(6.607)	(12.882)	(10.759)	(7.852)	(5.466)	(2.454)	(2.405)
Landholding (hectares)	5.997	3.959	0.187	0.138	2.169	1.552	10.809	7.997
	(62.467)	(51.285)	(1.891)	(1.549)	(31.036)	(25.913)	(85.471)	(74.669)

Note: Numbers in parentheses are standard deviations.

Table A3: Heckman Two-Step Estimates of Husband's and Wife's Wage Equation (6)

Variable Description	Lima		Other Urban Areas		All Peru	
	Husband	Wife	Husband	Wife	Husband	Wife
Constant	0.688	0.485	1.412	3.613	2.206	2.134
	(0.517)	(0.503)	(1.235)	(2.107)	(3.153)	(2.232)
Potential Work Experience	0.027	0.022	0.010	-0.062	0.006	0.003
	(0.634)	(0.475)	(0.168)	(0.703)	(0.157)	(0.076)
Potential Work Experience Squared	0.014	-0.018	-0.011	0.159	0.000	0.000
	(0.164)	(0.196)	(0.095)	(0.922)	(0.459)	(0.163)
Education:						
Years of Primary Schooling	0.091	0.150	0.016	0.273	-0.097	0.173
	(0.363)	(1.674)	(0.094)	(2.244)	(1.164)	(2.910)
Years of Secondary Schooling	0.094	0.105	0.111	-0.024	0.099	0.061
	(2.347)	(2.213)	(1.679)	(0.261)	(2.627)	(1.326)
Years of Postsecondary Schooling	0.032	0.017	0.086	-0.043	0.057	-0.019
	(0.749)	(0.263)	(1.663)	(0.450)	(1.464)	(0.343)
Vocational Training	0.128	0.347	-0.090	-0.144	0.113	0.127
	(1.267)	(2.427)	(0.626)	(0.819)	(1.194)	(1.071)
Secondary Technical Diploma	-0.032	-0.297	0.268	-0.400	0.082	-0.395
	(0.098)	(1.057)	(0.495)	(0.606)	(0.243)	(1.430)
Postsecondary Diploma	0.211	0.383	0.005	0.326	0.161	-0.058
	(0.622)	(1.241)	(0.020)	(0.876)	(0.707)	(0.225)
University Diploma	0.579	0.398	-0.154	-1.138	0.265	-0.289
	(2.614)	(1.232)	(0.672)	(2.447)	(1.385)	(0.967)
Public School	-0.303	-0.479	-0.242	-0.637	-0.175	-0.504
	(2.295)	(3.223)	(0.933)	(2.852)	(1.290)	(3.808)
Correlation between being married couple and wage errors	0.100	-0.187	-0.152	-0.119	-0.032	-0.273
	(0.620)	(0.886)	(0.531)	(0.325)	(0.209)	(1.573)
Correlation between both being in labor market and wage errors	-0.212	-0.148	-0.110	-1.082	-0.392	-0.837
	(1.137)	(0.520)	(0.670)	(3.371)	(2.686)	(3.084)
Residence - other urban area					-0.170	0.247
					(1.519)	(1.789)
Residence - rural area					0.094	0.391
					(0.486)	(1.757)
Sample Size	126	126	68	68	218	218
R^2	0.43	0.46	0.40	0.50	0.40	0.45

Note: Absolute values of t-statistics are in parentheses.

Table A4: Heckman Two-Step Estimates of Wage Equation (6) for the Restricted Sample Size of Men and Women

Variable Description	Lima		Other Urban Areas		All Peru	
	Male	Female	Male	Female	Male	Female
Intercept	0.467	1.400	1.476	0.562	4.030	0.300
	(0.479)	(1.849)	(1.399)	(0.376)	(3.590)	(0.483)
Potential Work Experience	0.076	0.043	-0.008	0.059	-0.041	0.067
	(2.569)	(2.338)	(0.200)	(1.272)	(1.077)	(4.528)
Potential Work Experience Squared	-0.126	-0.035	0.062	-0.046	0.103	-0.108
	(2.137)	(0.686)	(0.785)	(0.387)	(1.410)	(2.919)
Education:						
Years of Primary Schooling	0.032	0.080	0.019	0.148	-0.052	0.067
	(0.384)	(1.263)	(0.217)	(1.545)	(1.044)	(1.589)
Years of Secondary Schooling	0.094	0.127	0.179	0.055	0.060	0.136
	(2.843)	(4.044)	(4.526)	(0.579)	(2.052)	(4.569)
Years of Postsecondary Schooling	0.066	0.035	0.089	0.045	0.037	0.050
	(1.928)	(0.807)	(1.833)	(0.674)	(1.345)	(1.342)
Vocational Training	0.083	-0.033	-0.026	0.136	-0.231	0.160
	(0.804)	(0.194)	(0.148)	(0.866)	(1.555)	(1.490)
Secondary Technical Diploma	0.047	-0.217	-0.443	0.207	-0.340	-0.172
	(0.157)	(0.953)	(0.933)	(0.265)	(1.144)	(0.768)
Postsecondary Diploma	0.319	-0.253	-0.058	0.317	-0.284	0.183
	(1.198)	(0.889)	(0.177)	(1.047)	(1.004)	(0.906)
University Diploma	0.389	0.042	-0.280	-0.287	-0.112	0.138
	(2.517)	(0.151)	(0.964)	(0.790)	(0.517)	(0.653)
Public School	-0.241	-0.336	-0.290	-0.181	-0.326	-0.281
	(1.673)	(3.258)	(1.499)	(1.002)	(3.386)	(3.171)
Correlation between male wage earner and wage errors	0.282	0.307	-0.371	0.471	-2.180	-0.151
	(0.434)	(1.195)	(0.671)	(0.807)	(2.566)	(0.607)
Correlation between female wage earner and wage errors	0.248	0.214	0.274	0.366	0.096	0.203
	(1.055)	(0.776)	(1.340)	(1.076)	(0.640)	(1.034)
Correlation between joint participation and wage errors	-0.393	-1.150	-0.440	-1.000	-0.256	-0.398
	(1.287)	(3.086)	(1.353)	(1.672)	(1.221)	(1.369)
Residence - other urban area					0.258	0.070
					(1.459)	(0.562)
Residence - rural area					0.803	0.049
					(1.811)	(0.281)
Sample Size	332	315	145	128	535	502
R^2	0.39	0.35	0.46	0.48	0.42	0.37

Note: Absolute values of t-statistics are in parentheses.

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